

Online Research @ Cardiff

This is an Open Access document downloaded from ORCA, Cardiff University's institutional repository: <https://orca.cardiff.ac.uk/id/eprint/136948/>

This is the author's version of a work that was submitted to / accepted for publication.

Citation for final published version:

Qin, Jian, Li, Zhuoqun, Wang, Rui, Li, Li, Yu, Zhe, He, Xun and Liu, Ying
ORCID: <https://orcid.org/0000-0001-9319-5940> 2021. Industrial Internet of Learning (IIoL): IIoT based Pervasive Knowledge Network for LPWAN – concept, framework and case studies. CCF Transactions on Pervasive Computing and Interaction 3 , pp. 25-39. 10.1007/s42486-020-00050-2 file

Publishers page: <http://dx.doi.org/10.1007/s42486-020-00050-2>
<<http://dx.doi.org/10.1007/s42486-020-00050-2>>

Please note:

Changes made as a result of publishing processes such as copy-editing, formatting and page numbers may not be reflected in this version. For the definitive version of this publication, please refer to the published source. You are advised to consult the publisher's version if you wish to cite this paper.

This version is being made available in accordance with publisher policies.


See

<http://orca.cf.ac.uk/policies.html> for usage policies. Copyright and moral rights for publications made available in ORCA are retained by the copyright holders.





Industrial Internet of Learning (IIoL): IIoT based pervasive knowledge network for LPWAN—concept, framework and case studies

Jian Qin¹ · Zhuoqun Li² · Rui Wang³ · Li Li⁴ · Zhe Yu⁵ · Xun He⁵ · Ying Liu¹ 

Received: 18 October 2020 / Accepted: 21 November 2020
© The Author(s) 2020

Abstract

Industrial Internet of Things (IIoT) is performed based on the multiple sourced data collection, communication, management and analysis from the industrial environment. The data can be generated at every point in the manufacturing production process by real-time monitoring, connection and interaction in the industrial field through various data sensing devices, which creates a big data environment for the industry. To collect, transfer, store and analyse such a big data efficiently and economically, several challenges have imposed to the conventional big data solution, such as high unreliable latency, massive energy consumption, and inadequate security. In order to address these issues, edge computing, as an emerging technique, has been researched and developed in different industries. This paper aims to propose a novel framework for the intelligent IIoT, named Industrial Internet of Learning (IIoL). It is built using an industrial wireless communication network called Low-power wide-area network (LPWAN). By applying edge computing technologies in the LPWAN, the high-intensity computing load is distributed to edge sides, which integrates the computing resource of edge devices to lighten the computational complexity in the central. It cannot only reduce the energy consumption of processing and storing big data but also low the risk of cyber-attacks. Additionally, in the proposed framework, the information and knowledge are discovered and generated from different parts of the system, including smart sensors, smart gateways and cloud. Under this framework, a pervasive knowledge network can be established to improve all the devices in the system. Finally, the proposed concept and framework were validated by two real industrial cases, which were the health prognosis and management of a water plant and asset monitoring and management of an automobile factory.

Keywords Industrial Internet of Things (IIoT) · Edge computing · Low power wide area network (LPWAN) · Pervasive knowledge network · Machine health prognosis · Predictive maintenance

1 Introduction

At the age of Industry 4.0, industrial digital technologies (IDTs) have been developed rapidly (Maier 2017; Dopico et al. 2016), such as the Internet of Things (IIoT), artificial intelligence (AI), edge computing (Sittón-Candanedo et al. 2019), and pervasive knowledge (Deng et al. 2020). It requires the significant digital devices integrating into industrial systems, which has a high demand for data storing, transferring and analysing. For example, an automobile manufacturing company generally generated about 480 TB in 2013, which will be still increasing three-time by the end of 2020. Furthermore, the data was generated from different data sources, fused and nested together (Luckow 2015). In order to handle such a big and complex data, the conventional big data analytics methods have many challenges, such as high unreliable latency, high energy consumption,

✉ Ying Liu
Liuy81@Cardiff.ac.uk

¹ High-value Manufacturing Research Group, School of Engineering, Cardiff University, Cardiff CF24 3AA, UK
² ZifiSense, Charles Babbage Road, Cambridge CB3 0GT, UK
³ UNICMICRO, Science Town Commercial Plaza, Kexue Road, Guangzhou 510000, China
⁴ College of Electronics and Information Engineering and Shanghai Institute of Intelligent Science and Technology, Tongji University, Shanghai 201804, China
⁵ China Tower, Yuhui Masion, FuCheng Road, Beijing 100039, China

incomplete data fusion and poor security. The current industry needs a reliable, stable, and fault-tolerant data communication system and adequate real-time processing power for exploiting the hidden knowledge from it (Gai et al. 2016). At the meanwhile, the edge devices have become more potent and powerful in terms of high computing speed, ample memory space, and multiple embedded functions (Wang et al. 2020). It has pushed applications, data and computing power away from centralised points to locations closer to the user, which provides low latency, low energy consuming and secure support to delay-sensitive applications. Every edge of this IoT environment has the sufficient capability to learn and discover knowledge based on the big data and each other (Deng et al. 2020; Shi et al. 2016). The IIoT now has become a critical research topic for solving the industrial big data challenges.

The IIoT based framework, architecture, and taxonomy have been increasingly generated and published since the term of IIoT was firstly used (Boyes et al. 2018). According to the previous research, an IIoT system generally consists of four layers, which include device layer, network layer, service layer, and content layer (Hylving and Schultze 2013; Jansen and van der Merwe 2020; Hossain and Muhammad 2016). Data is collected on the device layer, transferred on the network layer, and then analysed on the service layer. Finally, the discovered knowledge is present on the content layer. These four layers commonly follow a logical sequence in the previous research when the framework is applied. However, with the rapid development of edge device and communication technology, the functions of these four layers are not distinguished specifically. Data can be analysed on the service, device and network layer. Furthermore, the different types and levelled knowledge is discovered pervasively, which will be presented to the users and also improves the performance of every point of the IIoT framework. There is a need in both academia and industry to realise how to achieve the above functions.

This paper aims to propose a novelty approach, Industrial Internet of Learning (IIoL), by delivering concept, introducing the framework and revealing case studies. This approach fully discovers the potential of the entire data network to solve the issues of data centralisation by the technologies of LPWAN and edge computing. In Sect. 2, relevant literature is reviewed to understand the state-of-the-art of LPWAN and edge computing technologies. Server LPWAN technologies are discussed and comprised. Also, edge computing is reviewed to compare to cloud and fog computing. Based on the understanding of LPWAN and edge computing, the IIoL is proposed in Sect. 3. The framework includes two main parts, the LPWAN part and the cloud part. The LPWAN consists of smart sensors and gateways. The raw data is sensed and collected from the industrial environment, such as production line, robots, and Computer Numerical Control

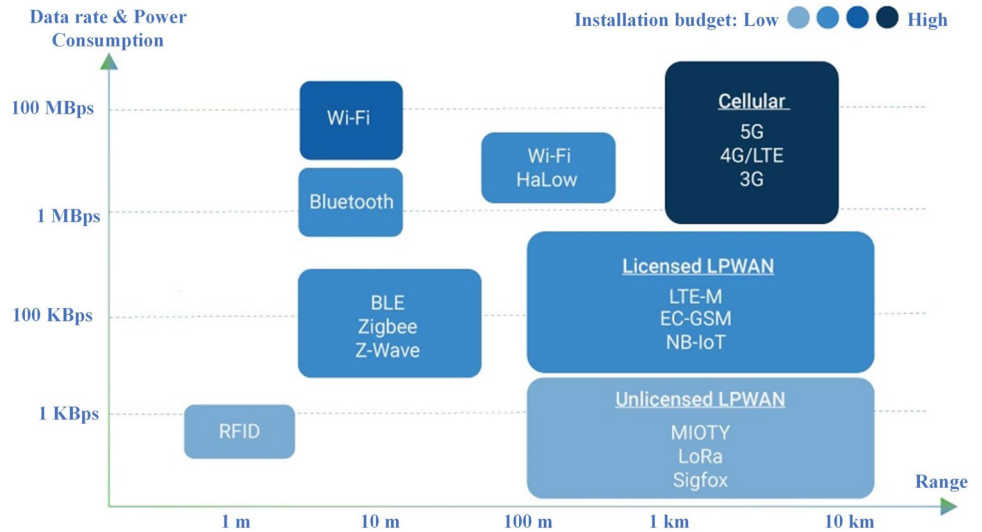
(CNC) machines, by smart sensors. Multiple dimensional data is integrated and pre-processed in smart sensors. Then the pre-processed information is sent to smart gateways which can discover the knowledge for smart sensors and the industrial environment. Finally, the processed data is processed and uploaded to the cloud, which means only the important processed information is uploaded to the cloud. The knowledge chains flow in the entire architecture, which creates a pervasive knowledge network. This approach has entirely realised the computing and data communication potential of edge devices and LPWAN. In Sects. 4 and 5, two cases, health prognosis of a water plant and automobile factor assets monitoring and management, are revealed to prove the feasibility of the proposed IIoL. Section 5 concludes.

2 Literature review

2.1 Data communication for LPWAN

The industrial communication used dedicated networks which were named as Fieldbus system in early days. This type of network was limited by parallel cabling between systems, sensors, actuators, and controllers (Sauter 2010). From the 1990s, the wireless networks became increasingly popular in the industry due to cables do not restrict it. These wireless networks were mainly adopted by the IEEE 802 protocol group (Tramarin et al. 2015). However, the main challenge of wireless networks was to ensure real-time and reliability capabilities, especially in the manufacturing environment (Vitturi et al. 2013). Wollschlaeger et al. (Wollschlaeger et al. 2017) believed that the Internet of Things (IoT) and Cyber-physic systems (CPS) would change the industrial scenery again because the concepts of IoT and CPS can fulfil the industrial requirement, e.g., regarding real-time, mobility, safety and security. They had also pointed out there were still some challenges in IoT and CPS current industry, such as hard time boundaries, isochronous communication, low jitter, high availability and low cost. In the current industrial environment, LPWAN became increasingly popular (Qin et al. 2019; Al-Sarawi et al. 2017) due to it offered affordable connectivity to industrial devices (Raza et al. 2017). In Fig. 1, the communication technologies are compared in two perspectives, data rate speed and range capacity.

Compared to other wireless communication methods, LPWANs generally has covered a big range. In this wireless communication technology group, several individual technologies are included, such as LoRa (Georgiou and Raza 2017), Sigfox (Zuniga 2016), Narrowband IoT (NB-IoT) (Ratasuk et al. 2016), and ZETA (Mekki et al. 2019). These four most popular LPWANs have various capabilities in terms of bandwidth, data rate, communication range,

Fig. 1 IoT communication technologies comparison

allow private network and standardisation, which are shown in Table 1.

The LoRa and NB-IoT are the two leading emergent LPWAN technologies (Sinha et al. 2017). ZETA is emerging which targets on reducing the energy consumption with the required communication quality of the network. It is currently popular in some Asian countries such as China and Japan (ZiFiSense 2020). From the above table, LoRa and ZETA have the most considerable bandwidth with a reasonable data rate. In contrast, the bandwidth and data rate of Sigfox is less than LoRa, NB-IoT and ZETA.

2.2 IIoT and edge computing: challenges and opportunities

The industrial big data refers to data generated in high-volume, high-variety, and high-velocity that requires high veracity to create high-value knowledge so-called five 'V' (Yin and Kaynak 2015). Generally, the industry generated data is upload to the factory management systems or the cloud, which is analysed by the centralised cloud computing technologies (Gonçalves 2015). It offers industrial organisations to centrally store massive amounts of data and optimise computational resources to deliver on their data

processing needs. The conventional centralised cloud computing is encountering severe challenges, such as unreliable latency, high energy consumption, and poor security (Shi et al. 2016).

Specifically, compared to the fast-developing data generation speed, the bandwidth of network has come to a standstill. With the growing quantity of data generated from IIoT, speed of data transportation is becoming a bottleneck for the cloud-based computing paradigm. For example, a typical automated manufacturing company generates 24 TB data per day, resulting in 13 billion data samples per day (GE 2012). If all the data needs to be sent to the cloud for processing, the response time would be a big issue. In some industry scenarios, The difference between a response time of 100 ms and 1 ms can be life-threatening (Bosch 2018). Secondly, big data could lead to an explosion in energy use. Nowadays, data centres use an estimated 200 terawatt-hours (TWh) each year and contribute around 0.3% to overall carbon emissions (Jones 2018). New alarming research suggests that data centres will be one of the biggest energy consumers on the planet, beating energy consumption levels in many countries. One of the most worrying models predicts that electricity is consumed by information communication technologies (ICT) could exceed 20% of the global (Andrae and

Table 1 Comparison between LoRa, Sigfox, NB-IoT and ZETA

	LoRa	Sigfox	NB-IoT	ZETA
Bandwidth	250 kHz	100 Hz	200 kHz	2 k H.Z.
Data rate	20 kbps	100 bps	200 kbps	600bps
Communication range	1 km (urban), 20 km (rural)	10 km (urban), 40 km (rural)	1 km (urban), 10 km(rural)	3 km (urban), 20 km (rural)
Private network	YES	No	No	YES
Energy consumption	Low	Low	Low	Very low
Standardisation	LoRa-Alliance	ETSI	3GPP	ZETA-Alliance

Edler 2015). With increasing applications installing on to the cloud, it may become untenable to meet the increasing energy demands. Thirdly, the security issue is another big challenge for using cloud computing. With as many IoT devices, smartphones, and other computing systems as there are available now, cyber-attacks against cloud platforms were mostly unthinkable. In present, not all cloud computing services can provide the high level network security. Some of the cloud solutions hardly deliver the required security between users, leading to shared resources, applications, and systems. Therefore, threats can originate from other users with the cloud service. Also, they target one user could also have an impact on other users (Kaufman 2009).

Motivated to solve these challenges, a new technology, edge computing, is driving a trend that shifts the function of centralised cloud computing to edge of networks (Ai et al. 2018). Similar to cloud computing, edge service providers furnish application, data computation, and storage services to the end-users. However, the edge services provide low latency, low energy consuming and secure support to delay-sensitive applications. Although edge computing has several advantages over cloud computing, the research on the emerging domain is still in its infancy (Khan et al. 2019). There exist three conventional edge computing technologies, cloudlet (Satyanarayanan et al. 2009), mobile edge computing (Hu et al. 2015) and fog computing (Bonomi et al. 2012). Mobile edge computing was defined by the European Telecommunications Standards Institute (ETSI) as an edge computing technology. It provides mobile users to use the computing service from the edge of the mobile network, within the Radio Access Network (RAN) and close to mobile subscribers (Hu et al. 2015). Cloudlet is a mobility-enhanced small-scale cloud data centre located at the edge of the network. The cloudlet supports resource-intensive and interactive mobile devices with lower latency. Different from the cloud, a cloudlet needs to be more agile in its configuration in order to associate with mobile devices. Also, the offloaded services need to be seamlessly migrated between cloudlets (Satyanarayanan et al. 2009). Fog computing extends the cloud computing paradigm to the edge of networks, wireless networks for the IoT. It is a highly virtualised platform that provides compute, storage, and networking services between end devices and traditional cloud computing data centres, but not exclusively located at the edge of network (Bonomi et al. 2012).

Li et al. (2019) proposed a resource scheduling approach for manufacturing systems on edge devices. This approach contained two aspects: selecting an algorithm for edge server (SA-ES) and cooperation of edge computing for low-latency task (CEC). The computing results were obtained based on the communication, computing and queuing time. In the experiments, the proposed approach was compared to cloud server computing and ordinary edge computing. The

validation results showed that the latency of the approach was the lowest with the lowest energy consumption generally. It was interesting that in the small data size task, the performance proposed approach was similar to ordinary edge computing. Comparing between edge and cloud computing, cloud computing was typically slower (30%) and consuming more energy consumption (50%). The paper also proved the resource scheduling was necessary for edge computing, which can provide lower computing latency and energy consumption.

Qi and Tao (2019) proposed several reference architectures of edge, fog, and cloud computing in smart manufacturing. These architectures were related to and independent of each other. The hierarchy architecture included three-level computing concepts, which edge computing was close to the real world. The fog computing was in between the edge and cloud computing with the medium speed, and cloud computing was on the top of the pyramid, which focused on the collaboration task with the high latency. In this article, three other architectures were provided for each of edge, fog and cloud, which could display their features and the development roadmap.

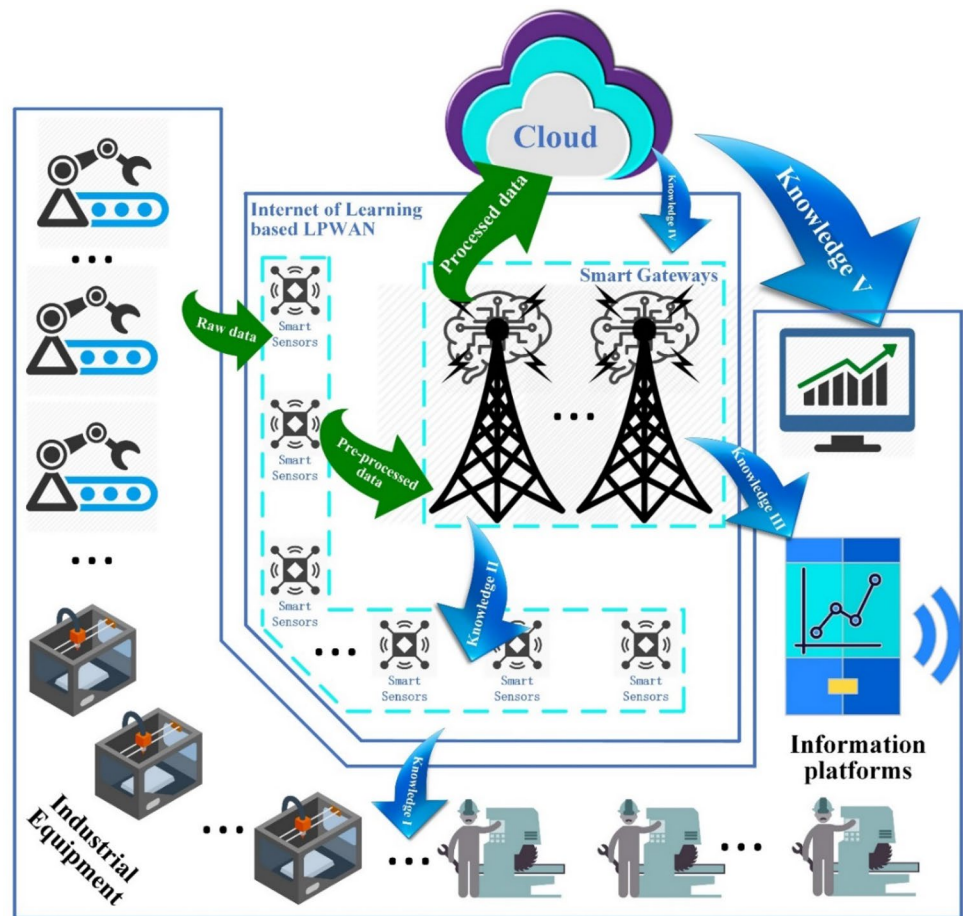
Besides, services on these three computing platforms can be summarised. Generally, on edge, the services are low intelligent compared to the fog and cloud. Nevertheless, the response time is much short, which can achieve real-time control. On the cloud, some high-level intelligent services are provided, such as task management, supply–demand matching, personalised customisation smart design collaboration and commerce collaboration. Authors tended to generate an overall structure for smart manufacturing including edge, fog and computing. Based on the capability and features, various levelled services are provided, which allows three-level computing technologies cooperated for achieving the requirement of smart manufacturing.

3 IIoL: pervasive knowledge network—concepts and framework

3.1 Concept and framework of IIoL

The IIoL architecture, shown in Fig. 2, consists of three main sections, physical section, LPWAN section, and cloud section. In the physical section, the industrial equipment, including industrial robots, computer numerical control (CNC) machines, and other industrial machines, are the primary data sources. The raw data is collected from these data sources by the smart sensors of the LPWAN section. Another critical part of the physical section is information platforms which provide the information and knowledge discovered from the cloud and LPWAN sections.

Fig. 2 The framework of ILoL



In the LPWAN section, this research proposes an internet of learning based framework for industry, which is called Industry internet of learning (IIoL). The smart sensors collect raw data from industrial equipment. The data is also pre-processed in smart sensors relying on the embedded processors. The pre-processed data is uploaded to the smart gateway, and low-level information, such as system status warning information is delivered to the physical section assisting the people in making corrected decisions. All of the pre-processed data is uploaded to the smart gateways, where the pre-processed data is analysed by some advanced data analytics algorithms, such as regression, classification, and clustering. The data is processed becoming more abstracted. Two types of knowledge are generated in the smart gateways. One knowledge is for smart sensors which improve the parameter settings in both software and hardware of smart sensors. Another knowledge will be present in the physical section, which focuses on the entire manufacturing system. For example, the twin models and machine health analysis is generated based on knowledge. In the proposed IIoL framework, only processed data is uploaded into the cloud. In the cloud, high-level data analysis, such as integrated simulation and synthesis, collaborative diagnostics and decision

making, is completed. Cloud-discovered knowledge can be used for improving the internet of learning based LPWAN. Generally, the proposed LPWAN, including smart sensors and gateways, have the learning capability from each other and the cloud. Additionally, on the cloud, AI knowledge, such as self-configuration, self-adjust, and self-optimisation, is discovered.

The proposed framework matches the structure and requirement of 5C architecture proposed by Lee et al. (2015), which is shown in Fig. 3. In the 5C architecture, five levels of functions are described as Sensor connection level, Data to information conversion level, Cyber level, Cognition level, and Configuration level, which are classified as three main technologies, Data technology, Analytic technology, and Operation technology. In the proposed structure, the smart sensors have mapped the functions in the Sensor connection level and Data to information conversion level. It is benefited from the edge device capabilities of data collection and processing. These capabilities are referred to the expected features of Data technology and Analytic technology defined for the 5C architecture, such as high data transfer rate, low latency, high reliability, data pre-processing and data visualization. The proposed smart gateways provide the

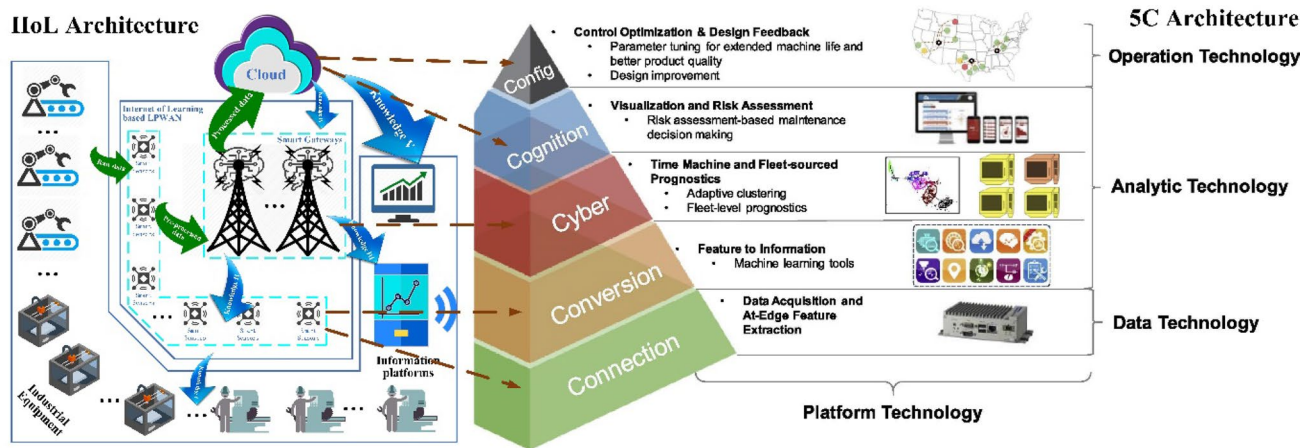


Fig. 3 The mapping between the proposed framework IIoL and 5C architecture (Lee 2019)

functions on Cyber level, which the analytic technology is applied. Furthermore, the cloud makes the manufacturing system intelligent and self-configured which are the core functions on Cognition level and Configuration level. In order to discover the hidden patterns and knowledge, Operation technology is used for achieving enterprise control and intelligent optimisation. Generally, the proposed framework includes the primary functions and features in 5C architecture (Lee et al. 2015). In the next section, the knowledge chains in this framework are examined and discussed with more details.

3.2 Pervasive knowledge network: IIoL-enabled LPWAN and cloud

Based on the computing capability of each edge in a proposed LPWAN network, including smart sensors and smart gateways, the knowledge is discovered and flowed between smart sensors and gateways. Integrating the cloud, there are

several knowledge chains in the proposed framework. In this section, the details of these knowledge chains are discussed. Before introducing the details of the methodology, the list of nomenclature is displayed in Table 2.

3.2.1 On smart sensors

The raw data is collected from the physical section by smart sensors which are represented as follows:

$$D = [D_1, D_2, \dots, D_r], \quad (1)$$

where D is the entire raw dataset which consists of the number of r features, D_1, D_2, \dots, D_r .

There are three types of knowledge for the physic work, Knowledge I, III, V which is discovered from smart sensors, gateways and the cloud. For Knowledge I, the based representation is shown as:

Table 2 The list of nomenclature which is used in the methodology

Symbol	Property	Symbol	Property
C^{KP}	Cloud obtained knowledge for the physical world (Knowledge V)	f_n^{ke}	The input variables of discovering knowledge II
C_m^{kf}	The knowledge for the smart gateway (Knowledge IV)	$f_{ke}(\cdot)$	The function of discovering the knowledge (II)
D_r	raw dataset, include the number of r features	F_m^{KC}	The processed data for cloud
E_n^{kp}	The edge obtained knowledge for the physic world (Knowledge I)	$f_{kc}(\cdot)$	The function of data processing for cloud
e_n^{kp}	The input variables of discovering knowledge I	f_m^{kc}	The input variables of data processing
E_n^{kf}	The data pre-processing results for the smart gateway	$g_{kp}(\cdot)$	The function of discovering the knowledge (Knowledge I)
e_n^{kp}	The input variables of data pre-processing	$g_{kf}(\cdot)$	The function of data pre-process
F_n^{KP}	The knowledge for the physic world (Knowledge III)	$h_{kp}(\cdot)$	The function of Knowledge V
f_n^{kp}	The input variables of discovering knowledge III	$h_{kf}(\cdot)$	The function of Knowledge IV
$f_{kp}(\cdot)$	The function of discovering the knowledge (III)	n	The number of smart sensors
F_n^{fe}	The knowledge for smart sensors (Knowledge II)	m	The number of smart gateways

$$\begin{aligned} E_1^{kp} &= g_{kp}(D, e_1^{kp}), \\ E_2^{kp} &= g_{kp}(D, e_2^{kp}), \\ E_n^{kp} &= g_{kp}(D, e_n^{kp}), \end{aligned} \quad (2)$$

where $E_1^{kp} \dots E_n^{kp}$ are the edge obtained knowledge for the physic world (Knowledge I), $g_{kp}(\cdot)$ is the function of discovering the knowledge for the physic world. n is the number of edge devices. $e_1^{kp} \dots e_n^{kp}$ are the variables of the function $g_{kp}(\cdot)$. Furthermore, the data is also pre-processed on smart sensors, which are defined:

$$\begin{aligned} E_1^{kf} &= g_{kf}(D_1^E, e_1^{kf}), & E^{KF} &= [E_1^{kf}, E_2^{kf}, \dots, E_n^{kf}], \\ E_2^{kf} &= g_{kf}(D_2^E, e_2^{kf}), & E^{FK} &= [E_1^{kf}, E_2^{kf}, \dots, E_j^{kf}], \\ E_n^{kf} &= g_{kf}(D_n^E, e_n^{kf}), & E_2^{FK} &= [E_{j+1}^{kf}, E_{j+2}^{kf}, \dots, E_k^{kf}], \end{aligned} \quad (3)$$

In the above functions, $E_1^{kf} \dots E_n^{kf}$ are the pre-processing results for the smart gateway, $g_{kf}(\cdot)$ is the function of discovering the knowledge for smart gateway. $e_1^{kf} \dots e_n^{kf}$ are the variables of the function $g_{kf}(\cdot)$.

3.2.2 On smart gateways

In the smart gateway section, two types of knowledge are discovered. One is for the physic world (Knowledge III), which the knowledge chain is represented as:

$$\begin{aligned} F_1^{KP} &= f_{kp}(E_1^{FK}, f_1^{kp}) \\ F_2^{KP} &= f_{kp}(E_2^{FK}, f_2^{kp}) \\ F_n^{KP} &= f_{kp}(E_n^{FK}, f_n^{kp}) \end{aligned} \quad (4)$$

In this set of functions, $F_1^{KP} \dots F_n^{KP}$ are the knowledge for the physic world (Knowledge III), $f_{kp}(\cdot)$ is the function of discovering the knowledge for the physic world. $f_1^{kp} \dots f_n^{kp}$ are the variables of the function $f_{kp}(\cdot)$. Another type of knowledge (knowledge II) is for smart sensors which the knowledge chains are denoted as:

$$\begin{aligned} F_1^{fe} &= f_{ke}(E_1^{FK}, f_1^{ke}) & f_1^{ke} &= [e_1, e_2, \dots, e_j] \\ F_2^{fe} &= f_{ke}(E_2^{FK}, f_2^{ke}) & f_2^{ke} &= [e_{(j+1)}, e_{(j+2)}, \dots, e_k] \\ F_n^{fe} &= f_{ke}(E_n^{FK}, f_n^{ke}) & f_n^{ke} &= [e_{n-2}, e_{n-1}, \dots, e_n] \end{aligned} \quad (5)$$

the $F_1^{KE} \dots F_n^{KE}$ are the knowledge for smart sensors (Knowledge II), $f_{ke}(\cdot)$ is the function of discovering knowledge. $f_1^{ke} \dots f_n^{ke}$ are the variables of the function $f_{ke}(\cdot)$, which is related to the inputs of smart sensor e . Meanwhile, in the smart gateways, the data collected from smart sensors is processed again for uploading to the cloud:

$$\begin{aligned} F_1^{KC} &= f_{kc}(E_1^{FK}, f_1^{kc}) \\ F_2^{KC} &= f_{kc}(E_2^{FK}, f_2^{kc}) \\ F_m^{KC} &= f_{kc}(E_m^{FK}, f_m^{kc}) \end{aligned} \quad (6)$$

$F_1^{KC} \dots F_m^{KC}$ are the processed data for cloud, $f_{kc}(\cdot)$ is the function of data processing for the cloud. The m is the number of smart gateways. $f_1^{kc} \dots f_m^{kc}$ are the variables of the function $f_{kc}(\cdot)$.

3.2.3 On cloud

On the cloud, the primary knowledge (Knowledge V) C^{KP} is for the physical world by using the function $h_{kp}(\cdot)$:

$$C^{KP} = h_{kp}(F^{KC}, \Delta^{kp}) \quad (7)$$

The inputs of $h_{kp}(\cdot)$ is the processed data obtained from the smart gateway. Also, the cloud can provide another knowledge (knowledge IV) for smart gateways based on the high-level information to improve the performance, which is represented as:

$$\begin{aligned} C_1^{kf} &= h_{kf}(F_1^{KC}, \Delta^{kf}) \\ C_2^{kf} &= h_{kf}(F_2^{KC}, \Delta^{kf}) \\ C_m^{kf} &= h_{kf}(F_m^{KC}, \Delta^{kf}) \end{aligned} \quad (8)$$

$C_1^{kf} \dots C_m^{kf}$ are the knowledge (knowledge IV) delivering to each smart gateway, where $h_{kf}(\cdot)$ is the knowledge discovering function, F_m^{KC} are the variables. In both expressions, Δ^{kf} and Δ^{kp} are the bias. According to the framework details shown above, five types of knowledge are discovered in the proposed framework. They have been summarised in Table 3, where the main contents, the target of the knowledge and the location of discovery are clarified

In order to validate the feasibility of the concept, framework and pervasive knowledge network, two cases are demonstrated in the next two sections. In the first case, the proposed framework was applied for the machine health

Table 3 The list of knowledge discovered by the proposed method

Knowledge type	Main contents	Target	Discovered on
Knowledge I	$E_1^{kp} \dots E_n^{kp}$	Physical world	Smart sensor
Knowledge II	$F_1^{KE} \dots F_n^{KE}$	Smart sensor	Smart gateway
Knowledge III	$F_1^{KP} \dots F_n^{KP}$	Physical world	Smart gateway
Knowledge IV	$C_1^{kf} \dots C_m^{kf}$	Smart gateway	Cloud
Knowledge V	C^{KP}	Physical world	Cloud

prognosis of a water plant. The plant consists of three pumping stations located in three different places, which over ten pump machines are installed in each pumping station. The vibration data of the pump machine is monitored, transferred and analysed for the predictive maintenance. The second case is about the automobile production factory assets monitoring and management. An over 200,000 square meters automobile production factory is focused. The status of laser rooms and assembly robots in this factory are monitored and controlled. The Predictive maintenance (PdM) is applied for the robots in this case. Both cases have been implemented in the real scenario, guided by the framework of the IIoL which the LPWAN of is based on the ZETA wireless communication technology. The data in these two case is collected from ongoing machines, systems, and working environment, which is used for improving and maintaining the relevant manufacturing systems.

4 Case study I: machine health prognosis and management of a water plant

4.1 Background

In this case, the machine health prognosis was analysed under the framework of the proposed IIoL approach focusing on a water plant which includes three pumping stations. These pumping stations are located in Shenzhen China, which has displayed on the following map, Fig. 4. The distance between the central station and west station is about 1.1 km, and the distance to the east station is about 0.35 km. The smart gateway is allocated in the central station. In each station, over ten water pumps are monitored by the smart sensors. The data is sensed, collected and pre-processed in each smart sensor. Then the pre-processed data is sent to the smart gateway for further analytics. The knowledge of

improving data collection and pre-processing return to the smart sensors. The essential information of urgent maintenance is displayed to the maintenance operators. These knowledge and information are also uploaded to the cloud for complete analytics. The advanced big data analysis, such as machine learning and deep learning, is applied to the cloud for machine health prognosis, which will also integrate more data and information out of the system.

4.2 Data pre-processing on smart sensors

The smart sensors used in the case study focus on collecting the vibration data representing the vibration of pumps. The sensor are mounted on each pump which connects to the smart gateway wirelessly in the ZETA network. Figure 5 shows the pumps in the pump station and the smart sensor mounted on the pump machine. The smart sensor is built on the STM32L452CC processor, which is an Ultra-low-power flex power control processor (STMicroelectronics 2019). The vibration sensor in the smart sensor is the micro-electro-mechanical systems (MEMS) vibration sensor, which is used for collecting the acceleration signals of three-axis, in terms of the x-axis, y-axis, and z-axis. There are 4096 sampling points collected by the sensor, where the data sampling frequency in this case study is 3200 HZ.

Based on the IIoL framework, the raw data is pre-processed on smart sensors. Only the pre-processed data is sent to the smart gateway. In this case study, 57 pre-processed features are generated on smart sensors, which have been determined in Table 4.

Apart from sending the pre-processed data to the gateway, the information of these features can be displayed on the user interface based on the interests of the operators and plant managers. The displayed information is referred to the Knowledge I in the proposed framework. In this case, the mean, maximum and minimum values of x, y, and z axes

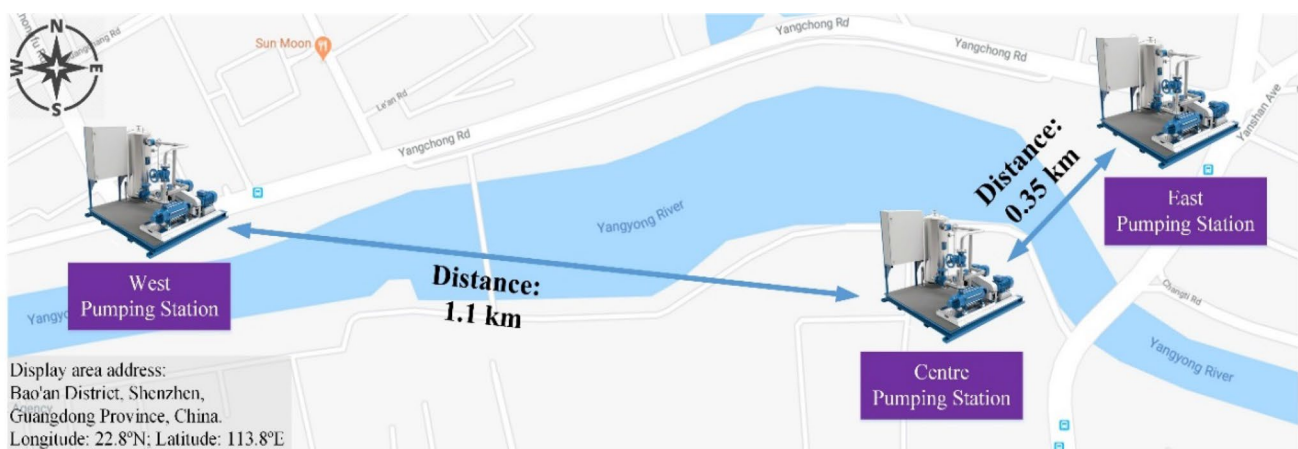


Fig. 4 Locations of pumping stations

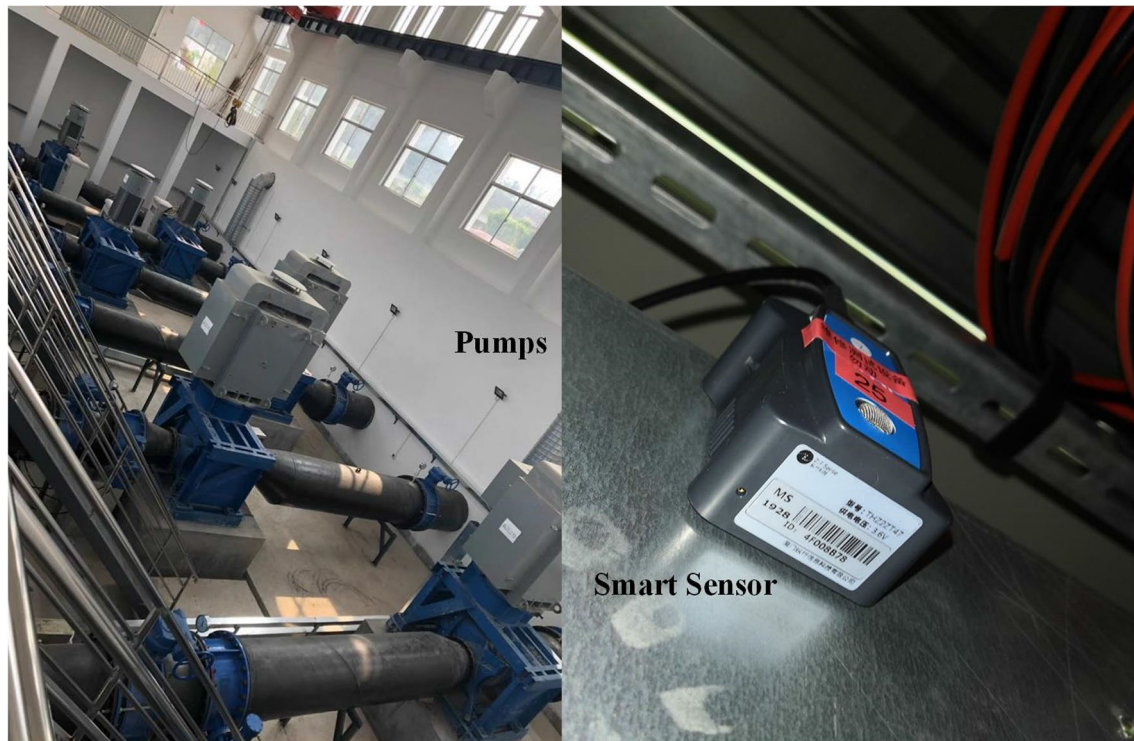


Fig. 5 Pumps (left) and smart sensor (right) in the water station

Table 4 Pre-processed features generated by smart sensors

Features	Description	Features	Description
meanX,Y,Z	Average in x, y and z axes.	peakX,Y,Z	Peak values in x, y and z axes
maxX,Y,Z	Maximum in x, y and z axes.	pulseX,Y,Z	Pulse Values in x, y and z axes
minX,Y,Z	Minimum in x, y and z axes.	marginX,Y,Z	Margin in x, y and z axes
rmsX,Y,Z	Root mean square in x, y and z axes.	skewRatioX,Y,Z	Skewness ratio in x, y and z axes
smrX,Y,Z	Standardised mortality ration in x, y and z axes.	kurRatioX,Y,Z	Kurtosis ratio in x, y and z axes
stdX,Y,Z	Standard deviation in x, y and z axes.	meanSpectrumX,Y,Z	Average of spectrum in x, y and z axes
varX,Y,Z	Variation in x, y and z axes.	centerSpectrumX,Y,Z	Centre point of spectrum in x, y and z axes
skewX,Y,Z	Skewness in x, y and z axes.	rmsSpectrumX,Y,Z	Root mean square of spectrum in x, y and z axes
kurX,Y,Z	Kurtosis in x, y and z axes.	stdSpectrumX,Y,Z	The standard deviation of spectrum in x, y and z axes
waveX,Y,Z	Wavelet in x, y and z axes.		

are displayed which gives plant operators and manager a general idea of the vibrations on three axes at the perspective of basic statistics.


4.3 Knowledge and information discovery on smart gateways

Technique details of the smart gateway are presented in Table 5. The smart gateway applies ATSM5D36 as the core processor. This processor uses ultra-low-power ARM Cortex A5 as the core, but it has a reasonable computing capability in terms of 536 MHz CPU speed and 128 KB

SRAM (Cortex-A5™ 2009). This smart gateway can cover over 5 km in the urban environment, which three pumping stations are built under the communication range.

On the smart gateway, all pre-processed data that is collected from pump machines will be integrated. The data from each pump machine is explicitly marked for identifying the machine. The clustering process is applied for realising the general machine behaviours, which are represented as different clusters on the smart gateway. The *K*-Means is used as the clustering algorithm in this case study (Jiang et al. 2020). Three clusters have been set up as the cluster number, which is based on three pump station. The outlier

Table 5 Technique details of the Smart gateway

 Smart gateway	Technique details	
	Transfer Protocol	ZETA
	Working frequency	Sub-GHz
	Core processor	ATSMA5D36
	Transmit power	≤20dBm
	Number of channels	Three channels
	Power supply type	PoE/AC100 - 240V to DC 5V
	stand-by current	≤100mA
	Maximum power	≤5W
	waterproof level	IP67
	Operating temperature	−20 °C ~ + 75 °C
	storage temperature	−30 °C ~ + 85 °C

data is then highlighted to present to the operator, which are represented as Knowledge III. The clustering results are also integrated into the dataset, which is uploaded to the cloud. Also, a feature selection process is used on the smart gateway for the clustering at the meanwhile. The most important features are determined out of pre-processed features. The entropy-based feature ranking is used, which the importance of each feature is outlined. To increase the processing capability of smart sensor, 80% features which are on the top of feature ranking, are used for pre-processing on the smart sensor. This knowledge (Knowledge II) is sent down to each smart sensor. However, it is dynamic information which is influenced by not only clustering on the smart gateway but also the results sent by the cloud, which will be explained in the next subsection.

4.4 Machine health prognosis on the cloud

By using the processed data, the health of each pump machine is predicted, especially for the critical component of a pump machine, the bearing. Based on the historical data and the domain knowledge, the health of each pump machine is levelled as a health score, which is 0–100. The 0 means the pump machine is no longer to be used, and 100 means the machine is new. This score is used as the main predicted target for machine health prediction, which is presented to the managers as Knowledge V. In this case, three prediction methods are used, which are linear regression, decision tree and neural network. Comparing the prediction accuracy of these three algorithms, the neural network obtained the highest accuracy. The predicted health score is presented to operators and system managers, which is used for understanding and maintaining the machine.

Furthermore, on the cloud, all the data is integrated, and the feature is ranked again. The feature selection results are sent to smart gateways, which improves the processing capability of the smart gateway. This knowledge (Knowledge IV) is also compared with the feature selection results of the smart gateway to enrich the understanding of the processed vibration features.

5 Case study II: assets monitoring and management for automobile factory

5.1 Background

The second case, designed under the IIoL framework is about the assets monitoring and management in an automobile factory in which the production area is over 200,000 square meters. In this case, two laser rooms and over 40 industrial robots are focused as the main targets. The working environment is shown in Fig. 6. The left image shows the cooling water status monitoring smart sensors and working environment for the laser room. The right image shows the smart sensor of robots, which can sense the temperature and vibration of industrial robots.

Several types of smart sensors have been installed for collecting data and data pre-processing due to the significant production area and the signal interference by the factory facilities. The smart gateway cannot cover the entire factory area within a reasonable network. To solve this issue, two mote devices are used in this case to enhance wireless communication strength and extend the communication range. The details of the mote devices are introduced in Sect. 5.3. By using the data collected from the

Fig. 6 The working environment of the automobile production factory



smart sensor and the proposed IIoL approach, the working environment and devices status is monitored and analysed, and the industrial robots are maintained predictively.

5.2 Data pre-processing on smart sensor

The smart sensor uses the same processor in this case. The details are shown in Sect. 4.3. However, more types of sensors are applied in this case. The features of the raw data are explained in Table 6. According to the table, the temperature and humidity of the laser room have been monitored inside and outside. For the industrial robot, the temperature of cooling water, the temperature and vibration of robot server motors are also monitored. Each smart sensor is connected with smart gateway wirelessly in the entire automobile factory.

Similar to case one, for each feature, 19 pre-processed features are generated on the smart sensor, which 133 features are generated and sent to the smart gateway in the LPWAN. Additionally, the mean, maximum and minimum values of the laser rooms in a period are presented to the operator with the alert as the defined Knowledge I. There are three colour alerts introduced in this case.

5.3 Knowledge and information discovery on smart gateways


To avoid the unnecessary data missing in the larger and complete working environment, this case uses the other device for enhancing the communication strength of the LPWAN, which is called mote. The mote is designed for extending and enhancing the LPWAN, which is a low power and battery support wireless network middleware, especially for some production factories and more substantial network range requirement. In this case, the mote details are shown in Table 7.

Comparing to a smart gateway, the mote abandons the computing capability but much lower the power usage, especially when it is standby, which allows the battery power supply. It has been approved as an indispensable component in the IIoT in this case study. After the pre-processed data is sent to the smart gateway via the mote, all the data is integrated and classified into different datasets, the laser room dataset and the industrial robot dataset. Similar to the last case, clustering is one of the primary data analysis methods used on the smart gateway, which is presented to the relevant users as the defined Knowledge III. The status cluster information

Table 6 Feature description

Laser rooms		Industrial robots	
Feature name	Description	Feature name	Description
laserTemp-in	Temperature of inside laser room	coolTem	Temperature of robot cooling water
laserTemp-out	Temperature of outside laser room	motorTem	Temperature of robot sever motor
laserHum-in	Humidity of inside laser room	motorVib	Vibration of robot server motor
laserHum-out	Humidity of outside laser room		

Table 7 Technique details of the mote

	Technique details	
	Transfer Protocol	ZETA
	Working frequency	Sub-GHz
	Transmit power	≤20dBm
	Power supply type	2*ER34615 (battery)
	Working current	≤70mA
	stand-by current	5μA
	waterproof level	IP67
	Operating temperature	−20 °C ~ + 75 °C
	storage temperature	−40 °C ~ + 100 °C

is integrated with the pre-processed data and uploaded to the cloud. Additionally, the feature selection method is also applied to the smart gateway in this case. The laser room and industrial robot features are selected separately. The selected feature knowledge (Knowledge II) is sent back to a smart sensor for improvement.

5.4 Factor assets monitoring and management on the cloud

After receiving the processed data from smart gateways, this data is integrated with historical data. Based on the laser room monitoring data and processed data, the laser room monitoring status is predicted. The predictive time window is set as 1 s. The time-series based neural network, long-short-term-memory (LSTM) network was used in this case study. Another primary function on the cloud is predictive maintenance of industrial robots. The processed data is used with robot historical maintenance dataset. This case targeted on the Remain useful life (RUL) of robots as the output of the modelling. A suitable modelling approach is explored to establish an airport conveyor RUL prediction model. Since there are multi-types of data in the integrated database, a merged neural network which consists of a long-short term memory network and artificial neural network is designed for modelling. A merged neural network can learn the hidden patterns from different data types and fuse these patterns to further learn the abstract patterns that relevant to the RUL of robots. The RUL information is display to the factory managers as Knowledge V. Also the RUL results can help smart gateway to improve feature selection, which is referred to as the defined Knowledge IV.

6 Discussion

In the last two sections, two industrial cases have been revealed to validate the feasibility of the proposed approach, IIoL. The IIoL has been implemented successfully in these two different industrial scenarios, which the working environment, situation and performance are different. In the first case, the pump machines health was presented, analysed and predicted to the operators and managers. The knowledge and data have been exchanged between the smart sensors and smart gateway, which improves the performance of LPWAN and Cloud sections. In the second case, the proposed method was applied in an even larger and more complete working area. Two types of industrial targets were focused on this case, the laser room and industrial robots. The industrial robots are maintained predictively benefiting from the proposed IIoL approach.

Although the working environment is different between the introduced case studies, there are still some commonalities. Both cases are located in a large and complicated working field, which is generally larger than hundred-thousand square meters. Furthermore, both cases have been surrounded by sophisticated electrical devices, which have caused signal interference. These two commonalities have shown the advantages of LPWAN, wide range and high stability. Additionally, this is a low power consumption network, which has a low cost of power consumption when the network is running. However, it is still the early stage of both cases, according to the principle of the proposed approach. Also, the cases are still developing following

the proposed framework to achieve the goals, mainly the functions on the cloud. More relevant data needs to be collected by integrating more sensors. The results of machine health prognosis and predictive maintenance are on the stage of the test, which is going to be used in reality soon.

Apart from the introduced industry case studies, the proposed approach can also be applied to another manufacturing system with some requirements. First of all, the smart sensors need a friendly interface to sense and collect essential data from the target system, which provides the system with a digital industrial environment. A suitable digital environment can show real-time data and information to the relevant people. Moreover, the target system needs to be covered by an LPWA network. In the above case studies, ZETA network has been implemented as the supported LPWAN technology in this research, which can be replaced as another LPWAN technology. The technology plan is based on the local wireless communication policy and infrastructure budget, which should be planned before applied the proposed approach.

7 Conclusions

IIoT is one of the core technologies at the age of Industry 4.0. The computing capability of current edge devices is sturdy and able to achieve some complex data processing. The LPWAN technologies can cover a large area with low power consumption, which is factory-suitable wireless communication technology. The focus of this paper has been on discovering the full potential of the IIoT network, which includes edge and network devices. A data and knowledge framework (IIoL) was proposed, which was inspired by a review of related research indicating the significant computing and data-communication capability of edge devices and LPWAN. In the proposed framework, every point of the network is used to generate relevant information and knowledge. The information and knowledge are exchanged between edge devices and gateways for improving the performance of the entire system. Two case studies are revealed in this paper. In the case studies, the feasibility of the proposed approach was carried out based on a pump station and automobile factory. Data was collected based on different purposes, and smart sensors and gateways were improved by the knowledge discovered from the proposed IIoL approach. On the cloud, functional models were built based on advanced data analytics technologies, such as machine learning and deep learning. The results are used for assisting relevant professionals in understanding the system and maintaining the critical component predictively. Finally, this approach bears the nature of data-driven which can also be developed to help many other manufacturing systems apart from the cases introduced in this paper.

Open Access This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit <http://creativecommons.org/licenses/by/4.0/>.

References

- Ai, Y., Peng, M., Zhang, K.: Edge computing technologies for Internet of Things: a primer. *Digital Commun. Netw.* **4**(2), 77–86 (2018)
- Al-Sarawi, S., et al.: Internet of Things (IoT) communication protocols. In 2017 8th International Conference on Information Technology (ICIT). IEEE (2017)
- Andrae, A., Edler, T.: On global electricity usage of communication technology: trends to 2030. *Challenges* **6**(1), 117–157 (2015)
- ARM, Cortex-A5™ Technical Reference Manual. 2009
- Bonomi, F., et al.: Fog computing and its role in the internet of things. In Proceedings of the First Edition of the MCC Workshop on Mobile Cloud Computing. 2012
- Bosch: Edge computing for IoT—a guide on how edge computing complements the cloud in IoT, B.S.I. GmbH, Editor. 2018
- Boyes, H., et al.: The industrial internet of things (IIoT): an analysis framework. *Comput. Ind.* **101**, 1–12 (2018)
- Deng, S., et al.: Edge Intelligence: the Confluence of Edge Computing and Artificial Intelligence. *IEEE Internet of Things Journal*, 2020
- Dopico, M., et al.: A Vision of Industry 4.0 from an Artificial Intelligence Point of View. The Steering Committee of The World Congress in Computer Science, Computer (2016)
- Gai, K., et al.: Dynamic energy-aware cloudlet-based mobile cloud computing model for green computing. *J. Netw. Comput. Appl.* **59**, 46–54 (2016)
- GE, The Rise of Industrial Big Data. GE Intelligent Platforms, (2012)
- Georgiou, O., Raza, U.: Low power wide area network analysis: can LoRa scale? *IEEE Wirel. Commun. Lett.* **6**(2), 162–165 (2017)
- Gonçalves, P., et al.: Adapting SDN datacenters to support Cloud IIoT applications. In 2015 IEEE 20th Conference on Emerging Technologies & Factory Automation (ETFA). 2015. IEEE (2015)
- Hossain, M.S., Muhammad, G.J.C.N.: Cloud-assisted industrial internet of things (IIoT)-enabled framework for health monitoring. *Comput. Netw.* **101**, 192–202 (2016)
- Hu, Y.C., et al.: Mobile edge computing—a key technology towards 5G. ETSI White Paper **11**(11), 1–16 (2015)
- Hylving, L., Schultze, U.: Evolving the Modular Layered Architecture in Digital Innovation: the Case of the Car's Instrument Cluster. 2013
- Jansen, J., van der Merwe, A.: A Framework for Industrial Internet of Things. Springer International Publishing, Cham (2020)
- Jiang, C., Wan, J., Abbas, H.: An edge computing node deployment method based on improved k-means clustering algorithm for smart manufacturing. *IEEE Syst. J.* 2020
- Jones, N.: How to stop data centres from gobbling up the world's electricity. *Nature* **561**(7722), 163–167 (2018)
- Kaufman, L.M.: Data security in the world of cloud computing. *IEEE Secur. Priv.* **7**(4), 61–64 (2009)
- Khan, W.Z., et al.: Edge computing: a survey. *Future Gener. Comput. Syst.* **97**, 219–235 (2019)

- Lee, J., Bagheri, B., Kao, H.-A.: A cyber-physical systems architecture for industry 4.0-based manufacturing systems. *Manuf Lett* **3**, 18–23 (2015)
- Lee, J., Singh, Azamfar, M.: Industrial artificial intelligence. arXiv preprint [arXiv:1908.02150](https://arxiv.org/abs/1908.02150) (2019)
- Li, X., et al.: A hybrid computing solution and resource scheduling strategy for edge computing in smart manufacturing. *IEEE Trans. Ind. Inform.* **15**, 4225–4234 (2019)
- Luckow, A., et al.: Automotive big data: applications, workloads and infrastructures. In 2015 IEEE International Conference on Big Data (Big Data). IEEE (2015)
- Maier, J.: Made Smarter Review. UK Industrial Digitalisation Review, 2017
- Mekki, K., et al.: A comparative study of LPWAN technologies for large-scale IoT deployment. *ICT Express* **5**(1), 1–7 (2019)
- Qi, Q., Tao, F.: A smart manufacturing service system based on edge computing, fog computing, and cloud computing. *IEEE Access* **7**, 86769–86777 (2019)
- Qin, W., Chen, S., Peng, M.: Recent advances in industrial internet: insights and challenges. *Digital Commun. Netw.* **6**, 1–3 (2019)
- Ratasuk, R., et al.: Overview of narrowband IoT in LTE Rel-13. *IEEE* (2016)
- Raza, U., Kulkarni, P., Sooriyabandara, M.: Low power wide area networks: an overview. *IEEE Commun. Surv. Tutorials* **19**(2), 855–873 (2017)
- Satyanarayanan, M., et al.: The case for vm-based cloudlets in mobile computing. *IEEE Pervasive Comput.* **4**, 14–23 (2009)
- Sauter, T.: The three generations of field-level networks—evolution and compatibility issues. *IEEE Trans. Industr. Electron.* **57**(11), 3585–3595 (2010)
- Shi, W., et al.: Edge computing: vision and challenges. *IEEE Internet Things J* **3**(5), 637–646 (2016)
- Sinha, R.S., Wei, Y., Hwang, S.-H.: A survey on LPWA technology: LoRa and NB-IoT. *ICT Express* **3**(1), 14–21 (2017)
- Sittón-Candanedo, I., et al.: A review of edge computing reference architectures and a new global edge proposal. *Future Generation Computer Systems* **99**, 278–294 (2019)
- STMicroelectronics, STM32L452xx datasheet. 2019
- Tramarin, F., et al.: On the use of IEEE 802.11 n for industrial communications. *IEEE Trans. Ind. Inform.* **12**(5), 1877–1886 (2015)
- Vitturi, S., Tramarin, F., Seno, L.: Industrial wireless networks: the significance of timeliness in communication systems. *IEEE Ind. Electron. Mag.* **7**(2), 40–51 (2013)
- Wang, X., et al.: Convergence of edge computing and deep learning: a comprehensive survey. *IEEE Commun. Surv. Tutorials* **22**(2), 869–904 (2020)
- Wollschlaeger, M., Sauter, T., Jasperneite, J.: The future of industrial communication: Automation networks in the era of the internet of things and industry 4.0. *IEEE industrial electronics magazine* **11**(1), 17–27 (2017)
- Yin, S., Kaynak, O.: Big data for modern industry: challenges and trends [Point of View]. *Proc. IEEE* **103**(2), 143–146 (2015)
- ZiFiSense. NEC Networks & System Integration Launches Enterprise IoT Platform Service Based on LPWA Standard "ZETA". 2020. <http://www.zifisense.co.uk/news/53.html>. Accessed 12 Jun 2020
- Zuniga, J.C., Ponsard, B.: Sigfox System Description. *LPWAN@ IETF97*, Nov. 14th, 2016. pp. 25 (2016)



tem integration, process monitoring and controlling, and advanced data analytics.



ecom regulators.



founded Unicmicro Co., Ltd. to provide innovative integrated circuits with solutions for industrial IoT (Internet of Things) and smart homes. Currently, he is also the Vice President of Guangdong Integrated Circuit Industry Association (China), the Vice President of Guangzhou Semiconductor Association, and the Vice President of Guangdong Investment Promotion Association. In April 2019, he initiated and established the ZETA China Alliance in Shanghai with the founding member ZiFiSense and was elected as the Chairman.

Jian Qin obtained his Bachelor in Mechanical Engineering from Hainan University, China in 2012, then MSc degree in Mechatronics from the University of Bath in 2014, and PhD from Cardiff University in 2020. His research focuses on system monitoring, processing controlling, manufacturing informatics for additive manufacturing (AM), and Industrial Internet of Things (IIoT). Based on his educational background and industrial experience, he is currently working on IIoT based AM sys-

Zhuoqun Li obtained his PhD from the University of Plymouth, UK and did his Post-Doc with the Imperial College London. He has more than 10 years' experience in telecommunication, working through operations, R&D and consulting functions. He is the founder & CEO of ZiFiSense, a leading IoT technology vendor that is known for the LPWAN standard – "ZETA." Previously, Dr Li had worked as a consultant with PA Consulting and acted as the Technical Advisor to the British and Dutch Tel-

Rui Wang is the founder, Chairman, and CEO of Unicmicro (Guangzhou) Co., Ltd. Before Unicmicro, he served as the Senior Vice President and the General Manager of VeriSilicon Holdings Co., Ltd. Since 1999, Mr Wang has been working in the microelectronics and telecommunications industries and has moved to the senior technical and sales management team in well-known American semiconductor companies such as Marvell, TranSwitch, Mindspeed, and Conexant. In 2017, he



Li Li is currently a Professor of Control Science and Engineering at the Tongji University, China. She has over 80 publications including 5 books, 30+ journal papers, and 2 book chapters. Her current research interests are in smart production, computational intelligence and autonomous intelligent systems.



Zhe Yu obtained his Master from Tongji University, China. Currently, he is the CEO of China Tower Intelligent Connectivity Corporation. He has more than 25 years' extensive experience in the telecom industry, specialized in the digital transformation of the mobile operators and the communication tower industry. His work has been recognized with more than three provincial and ministerial awards in China.



Xun He obtained his PhD in Management from the Renmin University of China. Currently, he is the Marketing Director of China Tower Intelligent Connectivity Corporation. His research has been published in more than 10 books and academic papers on management studies. His professional achievements have been recognized in three provincial and ministerial awards in China. Dr He is also an adjunct professor with the School of Business at the Renmin University of China.



Ying Liu received the bachelor's and master's degrees in mechanical engineering from Chongqing University, Chongqing, China, in 1998 and 2001, respectively, and the PhD degree from the Innovation in Manufacturing Systems and Technology Program, Singapore MIT Alliance (SMA), National University of Singapore, Singapore, in 2006. He was an Assistant Professor with the Department of Industrial Systems and Engineering, The Hong Kong Polytechnic University, from 2006 to 2010, and the

Department of Mechanical Engineering, National University of Singapore, from 2010 to 2013. He is currently a Reader with the Intelligent Manufacturing Group, School of Engineering, Cardiff University, Cardiff, UK, where he is also the Group Lead of the High-Value Manufacturing Group. His research interests focus primarily on design and manufacturing informatics, intelligent (smart) manufacturing, data mining, and machine learning, design methodology and process, product design and advanced ICT in design and manufacturing; in these areas, he has authored or co-authored over 140 scholarly articles, one edited book, and more than ten special issues. Dr Liu is on the Editorial Board of Advanced Engineering Informatics. He is an Associate Editor of the ASME Journal of Computer and Information Science in Engineering (JCISE), the IEEE Transactions on Automation Science And Engineering (T-ASE), Autonomous Intelligent Systems (Springer) and the Journal of Industrial and Production Engineering (Taylor and Francis).